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massachusetts institute of technology

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Gradual Incorporation of Information into Stock Prices: Empirical Strategies

Sara Fisher Ellison and Wallace P. Mullin[1]

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Abstract

JEL: G1, G14, C1

This paper explores environments in which either the revelation or diffusion of information, or its incorporation into stock prices, is gradual, and develops appropriate estimation techniques. This paper has implications both for event study methodology and for understanding the process by which stock prices incorporate information. Two environments are highlighted.

First, information is often not revealed in one announcement but rather through a process of gradual public revelation, which may not be completely observable by a researcher. We examine the effect of the evolution of the Clinton health care reform proposal on pharmaceutical stock prices. We estimate the expected path of market-adjusted pharmaceutical prices over September 1992-October 1993 by isotonic regression, and find that the major portion of the decline in stock prices occurred gradually, and did not correspond to identified news events.

Second, the trading process itself may incorporate private information into stock prices gradually. That is an implication of the Kyle (1985) model, in which one or a small number of informed traders use their market power over their private information to maximize profits dynamically. We use the functional form predictions from Kyle in our estimation, and the results from a sample of targets of tender offers are consistent with the model.

1 Introduction

Information moves stock prices. A vast literature has arisen to exploit and explain that fact. Most of that research has assumed that the information is released on a small set of observable dates, and has either assumed or established that the information is incorporated into stock prices immediately. This paper borrows from the existing theoretical literature to explore environments in which either the revelation or diffusion of information, or its incorporation into stock prices, is gradual, and develops appropriate estimation techniques for such settings. There are two broad motivations for this paper.

First, there is the relevance for event study methodology. Event studies, long a workhorse of financial economics, have now become a familiar tool to examine questions in regulation, industrial organization, and international economics. In these studies, the impact of some firm decision or public policy change is evaluated by examining the immediate stock market reaction to an *ex ante* identifiable set of news events. The efficacy of the event study hinges on identifying the times when information was released to the stock market. The gradual revelation or diffusion of information therefore poses a problem. If a researcher's event has already been fully or partially anticipated, then an event study may either erroneously assess the impact of the news as zero, or it may successfully detect an impact but underestimate its magnitude. And in some debates, the empirical magnitude is the chief concern. For example, an ongoing debate in corporate finance and industrial organization concerns the total private gains from mergers and acquisitions, and the division of these gains between targets and acquirers. Event studies are an important methodological tool in this debate, and may provide inadequate estimates of the magnitude of the impact of merger announcements if the gradual incorporation of information is not accounted for.

A second, independent, motivation is to examine the process itself by which stock prices incorporate information. One could be interested in the characteristics of the political process by which information about a legislative event, say, is revealed to the market. Another example of interest in the theoretical finance literature is how the trading process transforms private information known only to a small set of traders into public information known by all market participants and hence reflected in stock prices. Kyle (1985) offered a seminal model of how private information will be gradually incorporated into stock prices by a rational informed trader, a rational market maker, and liquidity or noise traders. Although Kyle's article has sparked a large theoretical literature,

we are not aware of any direct empirical implementations of Kyle or related models. Our focus, the generic modelling and estimation of gradual incorporation of information, and our econometric modelling will therefore differ from other work in this area.

The next section discusses three possible mechanisms by which information could be gradually incorporated into a stock price. In the subsequent sections we develop two of these mechanisms in greater depth by considering an appropriate empirical application and the corresponding econometric techniques.

The main output of this paper is, then, providing researchers with additional tools for handling gradual incorporation of information and demonstrating their use in two short applications of independent interest. In both applications we find significant evidence of gradual incorporation of information that is not captured by traditional event study methods. In addition we learn characteristics of the process through which this gradual incorporation takes place.

2 Three Mechanisms

The first mechanism, a simple one, is just that a piece of information is often not revealed in one announcement to any market participant but rather through a gradual process of public information revelation and resolution of uncertainty. We imagine the most common empirical setting for this mechanism would be legislative or political events. A recent such example, and one of our illustrating applications, is the effect of the Clinton health care reform proposal on pharmaceutical stock prices. Various news items surrounding health care reform, most notably the harsh criticism by President Clinton and Hillary Rodham Clinton of the high price of drugs, precipitated a significant decline in pharmaceutical stocks. But other information concerning the contents of the plan and its prospects for passage are identified less easily. In that case think of the information inherent in one "event," the evolution of the health care reform proposal, being gradually incorporated into stock prices as information leaked out and uncertainty was resolved. This first type of gradual incorporation is not the result of asymmetric information or an inefficient market, then, but the direct result of the gradual or sporadic flow of information, which is then, we assume, immediately incorporated into price.[1] We can say little about the resulting expected price path—it will be

[1]This is consistent with the *semi-strong* form of the Efficient Market Hypothesis. Stock prices fully reflect all *publicly* available information.

the direct result of the rate at which information is publicly revealed—other than the following two characteristics.[2] First, since we assume information is immediately incorporated into price as soon as it is revealed, the expected price path will take a step form. Second, the expected price path will be monotonic. This requires more explanation. Our concern is the effect of information inherent in one large "event" as the uncertainty is gradually resolved. After the resolution of all such uncertainty, that event has been revealed as an unambiguously positive or negative event, as either good news or bad news. Note that the *realized* price will certainly not be monotonic, but the *expected* price path, conditional on the *ex post* occurrence of the larger event, will be monotonic.

The second mechanism is based on the idea that a small group of informed traders may not want to trade so as to instantaneously incorporate their information into the stock price. One formal model of this mechanism is provided by Kyle (1985). In his model, the informed trader(s)[3] use their market power over this private information to maximize profits dynamically and only allow their information to gradually be incorporated into price. Here, information is revealed all at once, but only privately, to a group of insiders. Kyle shows that it is optimal for insiders to place orders for a stock so that the market maker's price converges to the value only by the "end of the world," *i.e.*, the formal, public announcement of the information. One implication we take from the Kyle model is a specific functional form prediction for the price path. We will depart from Kyle in some elements of our empirical implementation, however. The trading process could be influenced by additional factors, such as the presence of multiple informed traders or concerns about penalties for illegal insider trading,[4] so we try to formulate an econometric specification that is both tractable and robust. The most obvious (and perhaps even tautological) empirical setting

[2]There is some evidence on the time series pattern of information revelation. Mitchell and Mulherin (1994) find a relationship between the number of news announcements released daily by the Dow Jones and aggregate firm-specific returns. But this relationship is not particularly strong and is unlikely to provide a restriction on the price path in such settings as health care reform.

[3]Kyle deals explicitly with a single informed trader exercising monopoly power over private information. Other authors have also obtained the result of gradual incorporation of information into stock prices with extensions of the Kyle model to multiple informed traders. See, for example, Foster and Viswanathan (1996) and Back, Cao, and Willard (1997). The implications of multiple informed traders depend on the assumed information structure and the risk-aversion of the informed traders, however. Holden and Subrahmanyam (1992) find immediate incorporation of information in the limit when multiple informed traders receive identical information. Gradual incorporation occurs if informed traders receive heterogenous signals or are risk-averse.

[4]There is a relevant distinction between the informed trading of the Kyle model and illegal insider trading. Kyle's informed trader does not hide his trading (within the noise provided by liquidity traders) because of criminal penalties. Rather, such concealment maximizes the informed trader's intertemporal profits. In fact, in Kyle, the informed trader reveals all of his private information by the announcement date.

for such a mechanism is the case where there may have been illegal insider trading. One might be interested in the characteristics of the insider trading itself, or one may simply be interested in estimating the full effect of an event that has been at least partially anticipated by the stock market due to illegal insider trading. Our application is in the market for corporate control, in particular the stock market reactions experienced by the targets of tender offers.

The third mechanism is based on the idea that the amount of information incorporated in the price of a stock might be proportional to the number of traders who are informed and that some pieces of information might be disseminated gradually through word-of-mouth communication rather than immediately through CNN. (This mechanism depends on the premise that one informed trader cannot or does not trade in a manner that fully incorporates his information into the stock price. Perhaps he is liquidity constrained or risk-averse, or perhaps he hides his information in a Kyle-ian manner to exercise market power and maximize his profits.) The idea underpinning this mechanism is much more *ad hoc* than a model such as Kyle's, but here, too, we can can derive functional form predictions of the price path under certain conditions. Since we are assuming that the amount of information incorporated into price is proportional to the number of informed traders, we simply need to appeal to models of learning and their predictions about the number of informed agents over time to give us functional form predictions for our expected price path. The resulting "S-shaped" pattern is a robust empirical finding in studies of technological diffusion, as in Griliches (1957) and Davies (1979), and can arise in epidemic-type models in which information is spread by personal contact between traders. At a minimum, it serves as a tractable parametric form for the information incorporation process. A contemporary application may be the spreading of "tips" based on (illegal) inside information. As Stern and Jereski recount in *Forbes*, word-of-mouth tips can be an important source of information diffusion, especially in merger deals. As Klein reports:

> You start with a handful of people, but when you get close to doing something the circle expands pretty quickly. You have to bring in directors, two or three firms of lawyers, investment bankers, public relations people, and financial printers, and everybody's got a secretary. If the deal is a big one, you might need a syndicate of banks to finance it. Every time you let in another person, the chance of a leak increases geometrically.[5]

Another appropriate empirical setting might be studies of the early history of the stock market,

[5]Frederick C. Klein. "Merger Leaks Abound Causing Many Stocks to Rise Before the Fact." *Wall Street Journal*, July 12, 1978, pp. 1, 31, quoted by Keown and Pinkerton, p. 857.

since one hundred years ago a piece of relevant information might have taken several days to reach all interested parties. An illustration and estimation of the "S-shaped" diffusion pattern is contained in Ellison and Mullin (1995), and so the two applications we develop further in this paper will be based on the first two mechanisms.

Although we believe the three mechanisms we mention here are of particular interest and importance in a variety of empirical settings, they are only three of many possible such mechanisms. The recent theoretical finance literature would provide us with myriad models of gradual incorporation of information, each potentially leading to a different empirical implementation.

There is a small literature on event-study methodology that is related, but nonetheless differs from our three mechanisms and associated approaches. Ball and Torous (1988) address the situation of event-date uncertainty, in which the researcher knows that an event took place on a single day within some time period, but does not know which date. But in their setting the news event and its incorporation into stock prices occurs at a single, albeit unknown, date, rather than occurring gradually.

There are also a number of methods that applied researchers employ when worried about event-date uncertainty and/or gradual diffusion or revelation of information. For example, they may produce graphs of Cumulative Average Abnormal Returns (CARs) over multiple days before and after an event, or they may widen the event window so as not to miss the impact of the event. As Salinger (1992, 1994) notes, the latter procedure as typically applied results in incorrect standard errors, and he provides an appropriate correction.

Our approaches are not just equivalent to applying a larger window or period for cumulating returns. Rather, we *jointly estimate* the timing of information release and the effect of that information. This provides a coherent estimation strategy, adding power to hypothesis tests and aiding in the interpretation of results, particularly when we are able to exploit functional form predictions about the price path. Moreover, this provides us with the correct standard errors for inference. Additionally, our focus includes different questions than those typically addressed in event studies. We are concerned not only with the total effect of an event, but also with the process by which information affects prices.

3 Gradual Revelation and Legislative Evolution

3.1 Isotonic Model

Our first mechanism, by design, operates with few *a priori* restrictions, and would therefore most appropriately be estimated using nonparametric techniques. Recall that our conceptualization is that one major event will affect the stock price positively or negatively and that information about that event leaks out gradually. Therefore, although the realized price path of the stock over the relevant period will not, in general, be monotonic, we want to constrain the effect that gradual leakage of information of one event has to be consistently positive or negative and so constrain the expected price path to be monotonic. In other words, *conditional* on the event in question, any resolution of uncertainty about it will have an effect on the stock price of the same sign as the effect of the larger event. By constraining the expected price path to be monotonic, we are distilling out the stock price movements which reflect the resolution of uncertainty.

Contrast our situation for a moment with the case where the individual effects of a series of related small events, leaks, actions, or announcements are themselves of interest. Even if these events are related, they could have opposite effects on stock price. For instance, one small event might be an erroneous announcement ostensibly shedding light on the probability of a bigger event occurring, which is then corrected the next day, the correction being the second small event. One might be interested in the separate effects of those two small events, in which case restriction to a monotonic expected price path would be incorrect. For our purposes, however, those events are *ex post* noise which do not further inform the market about a larger event. Therefore, a monotonic expected price path is precisely the restriction we need to extract price movements which do reflect the informing of the market.

In addition, an individual stock may be influenced by common factors such as the overall stock market, so we will want to estimate a monotonic path of the *market adjusted* price of a stock. Also, consistent with our idea that discrete bits of information about a large event leak out over time and are then immediately incorporated into prices, we would like our estimate to take the form of a step function.

The appropriate estimation technique, then, is isotonic regression on market-adjusted prices. Isotonic regression is a estimation method which does not impose functional form restrictions on

the regression function but does impose more general shape restrictions: that the function be nonincreasing or nondecreasing and that the function take a step form. The isotonic regression is the function which minimizes the sum of squared deviations of the observations from the estimated regression function among the class of functions that satisfy the shape restrictions. Note that the shape restrictions implicitly impose some smoothness on the estimator so that the issue of choice of smoothing parameter, usually an important empirical consideration in nonparametric estimation, is not crucial here.

3.2 Clintoncare and Pharmaceutical Stocks

Our first technique is motivated by and suited for analyzing the gradual incorporation of information, as exemplified by legislative events. Our illustration comes from the health care reform efforts pursued in the first two years of the Clinton administration. The plan itself took shape gradually, and saw its political prospects evolve over a lengthy time period, two features that make it particularly well-suited for this exploration. We choose to focus on the impact on pharmaceutical companies as one of the stock market sectors most sensitive to details of the Clinton plan. Our sample consists of 13 publicly traded pharmaceutical companies, listed in Table 1.

Although much of the finance literature concerns the determinants of a security's return, in our first two settings it is more natural to consider the effect on the security's price. Since we nevertheless wish to control for movements in a security's price that are generated by its comovements with the overall stock market, we compute *market-adjusted* prices in the following way.

We form an equally weighted portfolio of the pharmaceutical stocks in order to average out the noise from firm-specific shocks. Using the returns on this portfolio, we then estimated an OLS market model over the 250 trading days ending October 30, 1991 and the 250 trading days beginning November 14, 1994.[6] The 768 trading days we omit from October 31, 1991 to November 11, 1994 constitute the potential reform period, and span the broadest possible definition of the Clinton health care reform period, from just before Harris Wofford won a US Senate seat in Pennsylvania on a health care reform platform, to just after the Republicans won the 1994 midterm Congressional elections. Our choice of sample period therefore allows us to estimate market model parameters

[6] In calendar time, this period runs from November 5, 1990 to October 30, 1991 and then from November 14, 1994 to November 8, 1995.

free from information leakage about health care reform.

We estimate the equation

$$(1) \quad R_{it} = \alpha_i + \beta_i R_{mt} + \nu_{it}$$

where R_{it} is the return on portfolio i and R_{mt} is the return on the CRSP equally weighted index for day t.[7]

We form prediction errors over the potential reform period:

$$(2) \quad A_{it} \equiv R_{it} - \hat{\alpha}_i - \hat{\beta}_i R_{mt}$$

where $\hat{\alpha}_i$ and $\hat{\beta}_i$ are OLS estimates from the market model estimation period. A_{it} is an indicator of abnormal performance, and we translate this into an adjusted price $p_{i,t}$ by the formula:

$$(3) \quad A_{it} = \frac{p_{i,t} - p_{i,t-1}}{p_{i,t-1}}$$

after having normalized $p_{i,1} = 1$. Intuitively, if all fluctuations in a stock's price during the potential reform period could be accounted for by market movements, then A_{it} would equal zero each day, and the market adjusted price $p_{i,t}$ would be flat, equal to 1 each day.[8]

For estimating the isotonic regression, we need to focus on a period in which a single "large event" unfolds. We choose the period during which the Clinton plan took shape, culminating in the official unveiling of the plan and initial Congressional testimony about it. The larger event, then, would be the revelation of the Clinton plan. We begin the isotonic regression on September 24, 1992, the date of Candidate Clinton's speech at Merck broadly outlining his plans for health care reform, which emphasized a market-based approach to reduce health care costs. But many details remained unspecified. The ending date for the estimation was October 4, 1993. We believe this date represented the political high-water mark for the Clinton health care proposal. As noted

[7]Employing the CRSP value weighted index as the market measure had negligible effects on the estimated market model parameters.

[8]This market adjusted price avoids some measurement problems raised in the literature. The standard measure of long run abnormal performance is the buy-and-hold abnormal return (BHAR), which is the difference between a firm's multi-period compounded gross return and the multi-period compounded gross return on a benchmark portfolio, such as the market. Mitchell and Stafford (1997) point out that the compounding in the BHAR formula means that the BHAR is increasing in the bolding period, the number of days of compounding, even if true abnormal performance exists over a short time interval. Our measure avoids this problem since we compound only the indicator of single period abnormal performance. A separate concern is that if $\hat{\alpha}$ was substantially removed from zero, then compounding could impart erroneous drift to our market adjusted prices. This is not a problem here, since $\hat{\alpha} = 0.000045$, with a t-statistic of 0.122.

by David Broder and Haynes Johnson in *The System* (1997), President Clinton had unveiled his specific proposal in an address to Congress two weeks before, and Hillary Rodham Clinton had just turned in an impressive performance on Capitol Hill. But political momentum stalled after October 3, 1993, with events in Somalia and Haiti, followed by concentration on NAFTA. The unravelling of the health care plan continued beyond that.

In selecting these start and ending dates, we are aware of some of the newsworthy items that we included within this period. In particular, in February and March 1993, rumors circulated that the Clinton Health Care Reform Task Force, which was operating in secrecy, was going to include regulation of drug prices in its plan. Such fears seem supported by statements by President Clinton and Hillary Rodham Clinton attacking the high prices of vaccines and other pharmaceuticals. We know from contemporaneous accounts that these statements triggered a fall in pharmaceutical companies stock prices, but we do not use that information in the estimation.

Figure 1 summarizes the isotonic regression by graphing the estimated path of market-adjusted pharmaceutical prices over this time.[9] The upper and lower bands of Figure 1 represent the 95 percent pointwise confidence intervals for this estimation. Several features are noteworthy. First, pharmaceutical companies lost a considerable amount of (market-adjusted) value. The market adjusted price fell from .647 to .365 in a little over a year, a loss of 43.6 percent. Interpreting this value loss is simplified when one realizes that the market model $\hat{\beta}$ for the pharmaceutical portfolio was nearly 1, and the $\hat{\alpha}$ nearly zero.[10] So in this case the market adjusted price essentially represents the dollar payoff from forming an arbitrage portfolio that invested a dollar in the pharmaceutical portfolio and shorted the market by an equal amount. This investment strategy would have lost more than 43 cents over the year the Clinton plan evolved.

Second, the time-series is interesting in light of the coinciding political developments. Prices decline during the fall Presidential campaign in the aftermath of the Merck speech, and continue to decline dramatically through Clinton's election and his inauguration. Additional decline becomes less dramatic not long after the Clintons' attacks on the drug companies. The isotonic regression suggests that even if those attacks added news, the news confirmed a suspicion that was already

[9] We are grateful to Jason Abrevaya for his assistance with this technique. The isotonic regression is computed with the "Up-And-Down Blocks" Algorithm. See Barlow et al. (1972), p. 72. We compute associated standard errors through bootstrapping. The standard errors for isotonic regression were derived analytically by Groeneboom (1993), however.

[10] $\hat{\beta} = 0.9835$, with associated standard error of 0.0713, and $\hat{\alpha} = 0.000045$, with standard error of 0.00037.

partially reflected by the stock market. The middle of the graph displays a lengthy flat period which roughly corresponds to the latter period of the operation of the Health Care Task Force. When the Task Force disbands at the end of May, 1993, the decline in prices resumes, but at a slower rate than before.

Given that we can identify this series of potentially important events from contemporary news accounts, a natural alternative to the estimation above would be to perform a series of traditional event studies, cumulate the resulting estimated effects on stock prices, and compare that total effect to the total effect that we estimate from the isotonic regression. Table 2 presents results for the nine events listed with Figure 1, using a one-day event window.[11] When we cumulate the effects of these individual events, allowing for compounding, we obtain a total loss of 8.1 percent (with standard error 2.8 percent) compared with the estimated loss from the isotonic regression of 43.6 percent.

Although these identified events were jointly significant in their impact, the traditional event study misses a multitude of events—subtle shifts in public perception, the gradual filling in of plan details and unveiling of political positions, and therefore misses these events' impact. While our procedure cannot identify these events either, it can reflect the information content of these events on stock prices.[12]

Another alternative would be simply to plot the CARs or market adjusted prices over time. By imposing monotonicity and conducting an isotonic regression, we extract fundamentally different information from the data than a CAR plot can reveal.[13] Since we are concerned with the *expected* price path, conditional on the gradual realization of one "larger event," either good or bad news, imposition of monotonicity is not merely a restriction that we are willing to live with to gain

[11]One might worry that we have unfairly handicapped the traditional event study by only allowing for one-day windows. In fact, the results, both in magnitude and statistical significance, are strongest for one-day windows relative to three-, five-, and seven-day windows.

[12]Willard, Guinnane, and Rosen (1996) actually identify events from an asset price series by estimating breakpoints in the series, in a sort of "reverse event study." While related to our technique here, the purposes are quite different. Their purpose is to identify important events which might have been unobserved by the researcher. Ours, rather, is to identify price movements not necessarily related to important events, observed or unobserved, but perhaps due to more subtle changes in public information.

[13]Although applied researchers concerned with gradual diffusion often produce CAR graphs, there is a danger in conducting "eyeball econometrics." As Brown and Warner (1980) note, "in the absence of a plausible *a priori* reason for doing so, it is dangerous to infer the frequency distribution of the time of abnormal performance by merely looking at CAR plots and the estimated level of abnormal performance in each event-related [period]; if one puts enough weight on 'outliers', the null can always be rejected."

efficiency. Rather, it is the restriction we *must* impose in order to extract information about the pattern in which an *ex post* positive or negative piece of information moves a stock price.

4 Trading Process and Merger Leakage

4.1 Kyle Model

Our empirical implementation of the second mechanism will be based on a discrete-time dynamic version of Kyle's model. In this model, time t runs from 0 to 1. Roughly following Kyle's notation, we denote the position in the asset of the insider at time t as x_t and the price of the asset at time t as p_t. The noise trader's position in the asset at time t is u_t, where $\Delta u_t = u_t - u_{t-1} \sim \mathcal{N}(0, \sigma_u^2)$. In addition, let v be the liquidation value of the asset (which the insider learns at time 0). The equilibrium, in which the insider maximizes total profits, is characterized by the following linear relationships:

$$\Delta x_t = \mu_t(v - p_{t-1})$$

$$\Delta p_t = \lambda_t(\Delta x_t - \Delta u_t),$$

where μ_t and λ_t are constants which depend on time, and $\Delta x_t \equiv x_t - x_{t-1}$, $\Delta p_t \equiv p_t - p_{t-1}$.

Substituting the volume equation into the price change equation yields

(4) $\quad \Delta p_t = \delta_t(v - p_{t-1}) + \epsilon_t$

where $\epsilon_t = \lambda_t \Delta u_t$ and $\delta_t = \lambda_t \mu_t$. Expected price changes are positive if the previous period price is below the value of the asset, but the realization of the level of noise trading also influences realized prices. The independent error term has mean zero and a variance which may depend on t (through λ_t). See Figure 2 for a picture of the expected price path with *zero* realizations of noise trades. Still remaining is the characterization of the constants λ_t and μ_t and the nature of their dependence on t.[14]

Intuitively, the dependence of λ_t and μ_t on t reflects an "end of the world" effect: as the end of the world (and, therefore, the end of opportunities to profit) approaches, the insider will become

[14] Here we depart somewhat from the model. We do not solve the difference equations which describe the relationship among several constants in the equilibrium and obtain expressions for λ_t and μ_t. Instead we will make some computationally convenient assumptions about their dependence on t which preserve the salient features of the equilibrium.

more sensitive to the difference between v and p_{t-1}. At the end of the world, there is no longer an incentive to hide behind the noise trader, so the insider should grab all profits possible, thus closing the gap between v and p_{t-1}. Clearly, we want $\delta_t = \lambda_t \mu_t$ to be positive and increase as t increases.[15] Let $\delta_t = \gamma_1 + \gamma_2 t$. Then

$$(5) \quad \Delta p_t = \gamma_1(v - p_{t-1}) + \gamma_2(v - p_{t-1})t + \epsilon_t$$

Note we will not specify a functional form for λ_t alone, even though it multiplies Δu_t to give us the error term in the equation. We will, instead, allow for heteroskedasticity when estimating the equation to accommodate different types of dependence of ϵ_t on t. We now have an equation that can be estimated econometrically given values for p_t and v. We observe p_t, of course, and will use the price of the asset at the announcement date for v.

A few additional issues remain in the empirical implementation of the model. First, the correspondence between the timing in the model and in an empirical example must be established. Time 1, the announcement date (or "end of the world"), is clear, but time 0, the date at which the insider becomes informed, is unknown to the econometrician. We will need to estimate it.

Note that before time 0, $\gamma_1 = \gamma_2 = 0$ and $\lambda = 1$. In other words, price change in regime A, before information leakage, will be determined by the following equation:[16]

$$(6) \quad \Delta p_t = \Delta u_t$$

Price change in regime B, after the insider becomes informed, will just be given by equation (5).

We translate the timing in the model into calendar time. Calendar time covers days $t = 1, 2, 3 \ldots T$, having re-scaled t. The insider becomes informed on date t_0, $1 \leq t_0 \leq T$, and the information is publicly announced on date T. Finally, we will use a continuous approximation to an indicator function for the shift to regime B to maintain differentiability with respect to all of the parameters.

Given these adjustments, if X stands for the matrix of all the explanatory variables and θ for the vector of parameters, then the conditional mean function

[15]Were we to stay strictly within the confines of the Kyle model, we would want $\delta_t \longrightarrow \infty$ as $t \longrightarrow 1$, but practical considerations not included in the model, such as the threat of prosecution from insider trading, would presumably place an upper bound on δ_t. Also, it will be easier computationally to specify a δ_t that does not go to infinity.

[16]We assume here that the insider is not a noise trader before he becomes informed. Otherwise, Δp_t will be the sum of *two* independent errors and will have a variance greater than that of Δu_t alone.

$$(7) \quad m(X,\theta) = \xi_0 + \gamma_1(v - p_{t-1})f(t,t_0) + \gamma_2(v - p_{t-1})(\frac{t-t_0}{T-t_0})f(t,t_0)$$

where $f(t,t_0) = \frac{e^{(t-t_0)}}{1+e^{(t-t_0)}}$. Finally,

$$(8) \quad \Delta p_t = m(X,\theta) + \epsilon_t$$

where $\epsilon_t \sim \mathcal{N}(0, \lambda_t^2 \sigma_u^2)$. We estimate the parameters by Non-Linear Least Squares (NLLS).

We should emphasize that our goal in empirically implementing the Kyle model is not a full structural estimation of the model or an explicit testing of its implications. Rather we simply aim to exploit its simple and robust structure as a way to identify gradual incorporation of information. The important features we take from it are the relevant variables and the functional form of the relationship among them. These features then guide our estimation and provide us with additional power to the extent they are correct.

4.2 Merger Targets

Mandelker (1974) and Halpern (1976) both documented positive run-ups in cumulative excess returns of acquired firms ahead of the announcement date of takeovers and mergers. Since they used only monthly data, they may have missed a large part of this effect. Keown and Pinkerton (1981) were the first to use daily returns to explore this pre-announcement leakage. They find that the cumulative average residual of acquired firms becomes positive (but not necessarily statistically significant) 25 trading days before the announcement date. About one half of the total increase in cumulative average residuals occurs before the announcement date. The daily average residuals "are significantly different from zero at a minimum significance level of .90 on 10 of the final 11 days prior to the announcement date, the final 5 days significant at the .995 level."[17] Keown and Pinkerton interpret their results as supporting "pervasive" insider trading. Price run-ups of this type have subsequently been verified by many authors using many samples, although the interpretation of this fact is disputed. Jarrell and Poulsen (1989) for example attribute the run-up to speculative activity based on public information rather than to illegal insider trading.

Our goal in this section is not directly related to this insider trading debate. Rather, we implement a simple variant of the Kyle model, and we can therefore examine whether the price

[17]Keown and Pinkerton, p. 863.

pattern is consistent with this model of informed trading. Moreover, the restrictions imposed by the model can give us a more powerful method of detecting pre-event abnormal performance than merely cumulating abnormal returns over the pre-event period.

Our sample of targets consists of a 107-firm subsample from Jarrell and Poulsen's (1989) study of tender offers.[18] These firms are shown in Table 3. Jarrell and Poulsen's sample consists of 172 (successful) cash tender offers from 1981 to 1985 in which the target was traded on the AMEX or NYSE.

Jarrell and Poulsen identify and distinguish the "news-adjusted date" from the formal announcement date. "Specifically, the news-adjusted date is the earlier of:

1. the day before the formal *Wall Street Journal* announcement of a 14D-1 filing or tender offer proposal, or the day of the ticker announcement if before close of trading (the "formal" date), or

2. the public disclosure (usually over the Dow Jones ticker) of a Schedule 13D filing with a possible intention to seek a change of control, or

3. the public announcement of merger talks naming the target firm."[19]

For our sample, we use 107 of the 108 tender offers in which the "news-adjusted date" was the same as the formal announcement date.[20] In other words, we estimate the gradual incorporation of information in an environment in which we can be reasonably confident of the date at which the information became public.

We adjust the procedure for computing market-adjusted prices because announcement dates differ across firms. We use the formal announcement date in the Jarrell-Poulsen appendix for each target.[21] For each firm, we estimate an OLS market model over the 250 trading days from 310 trading days before to 61 trading days before the announcement date. We then form prediction

[18]Note that examining a sample of firms instead of one affords us several advantages. First, we gain statistical power. Second, we can make more general statements about the average time at which leakage occurs in addition to statements about the dispersion of those times. Finally, the problem of possibly nonstandard distributions of test statistics is mitigated as the number of firms grows relative to the number of time periods.

[19]Jarrell and Poulsen, pp. 231-232.

[20]We excluded one firm, Breeze Corp. (BRZ), since trading in its stock was suspended well before its announcement date.

[21]In five cases, the target did not trade on its announcement day. For these five (CEQ, CNG, DWR, RED, and TG), we substitute the next day each stock traded.

errors over the period from 60 trading days before the announcement up to the day after the announcement, and compute market-adjusted prices as described for the pharmaceutical portfolio. We use the market-adjusted price the day after the announcement as our estimate of the liquidation value v, since by that date all investors should know the news conveyed by the tender offer. By beginning estimation of the Kyle model at 60 days before the announcement date, we include more pre-announcement days than is typical in event studies of targets.[22] This choice is designed to accommodate a reasonably lengthy diffusion process while attempting to avoid including extraneous innovations far removed from the announcement date.

As an initial, descriptive regression, we regress Δp_t on the variable $(v - p_{t-1})$ interacted with dummy variables for the six 10-day periods preceding the announcement date. This reveals how strong an explanatory variable $(v-p_{t-1})$ is in different time periods leading up to the announcement date. The OLS estimates are reported in Table 4, and the pattern is consistent with a gradual and increasing leakage of information about the true liquidation value of the stock, and with predictions of the Kyle model. The coefficient estimates increase monotonically as the announcement date approaches, and the estimates are statistically significant in each time period.

Returning more formally to the conditional mean function in equation (7), we set $\gamma_2 = 0$ and estimate this restricted model by constraining the remaining parameters to be equal for all the firms. The results of NLLS estimation of the restricted Kyle model are reported in Table 5. The constant term, ξ_0, is small and is not statistically significantly different from zero, which is the value predicted by the theory. The coefficient γ_1, which measures the sensitivity of price changes to $v - p_t$, is positive and very statistically significant, also as predicted by the theory. Finally, t_0, the estimated date at which the insider receives his information, is just under 47.8 in this 60-day sample period, corresponding to 12.2 trading days before the announcement. The 95 percent confidence interval around the estimated t_0 ranges from day 46.58 to day 48.99. Both the point estimates and the confidence interval involve days that are somewhat closer to the announcement date than one might expect from some of the existing literature on merger targets, but are nonetheless reasonable. Strikingly, Meulbroek (1992) provides direct evidence on trading activity from public and non-public SEC data from illegal insider trading cases. In her sample, "on average, insider trading takes place

[22] Bradley, Desai and Kim (1988) and Jarrell and Poulsen use 20 days, Dodd (1980) uses 40 days. Keown and Pinkerton (1981) use up to 125 days, but their results suggest that the run-up in the target's price does not begin until 25 days before the announcement.

13.2 trading days (median=6.0) before the inside information is publicly announced."

In the next specification, we include both $(v - p)$ and $(v - p)t$ as regressors. The results are reported in Table 6, and they are further confirmation of the implications of the Kyle model.[23] In particular, γ_2, the coefficient on $(v-p)$ interacted with time, is positive and statistically significant. The coefficient γ_1 is also positive but is not statistically significant. Note however that the two explanatory variables are highly collinear and the F-test on the joint hypothesis that both γ_1 and γ_2 are zero is overwhelmingly rejected.[24] This pattern is directly implied by the Kyle model; the theoretical parameter δ_t, the coefficient on $v - p_{t-1}$ in the model, is increasing in t. Finally, the estimate of t_0, at 46.04, is not far removed from that found in the restricted model, although the precision is reduced.

These specifications have imposed that t_0 be equal across all firms, and so what we have estimated could be interpreted as the average value of t_0. One may, however, be interested in the dispersion of t_0 across targets. Our final model, then, is analogous to the Table 5 specification, except we estimate a separate transition time t_0 for each firm. First, our estimates of ξ_0 and γ_1 are fairly robust to this change in specification. The estimate of ξ_0 is still small ($\hat{\xi}_0 = -0.0012$) but now statistically significant at the 5 percent level ($SE = .0004$). The estimate of γ_1 is quite close to that in Table 5 ($\hat{\gamma}_1 = 0.0277$) and is very significant ($SE = .0017$).

The 107 remaining estimated parameters from this model, hard to interpret in table form, are presented in Figure 3 as a histogram.[25] Before interpreting these results, it should be noted that this is a histogram of *estimated* firm-specific transition times, as distinct from a histogram of *true* firm-specific transition times. In particular, the underlying distribution of estimated times will have a higher variance than the underlying distribution of true times because each has a positive standard error associated with it. Our estimated times have an average standard error of 7.6.

With that caveat in mind, we point out a few interesting features of this histogram. First, we have significant heterogeneity in our estimated times. Second, the bulk of our estimated times lie between approximately 30 to 45 days, or 30 to 15 days before the announcement. Most of

[23]The results we report were obtained from a wide range of reasonable starting parameter values. For large starting t_0 values the estimates converge to the degenerate case of $t_0 \simeq 60$.

[24]The value of $F(2, 6416) = 85.26$, with a p-value of 0.0000.

[25]In estimating this 109 parameter model with NLLS, we obtained convergence according to standard default criteria. However, the objective function was sufficiently flat in the directions of some of the parameters that standard errors could not be obtained for them. We have omitted those estimates from the histogram.

the existing merger literature assumes or finds that leakage begins in that range. Finally and perhaps most interestingly, the histogram has two significant nodes, the main one between 30 and 45 days and the second one much closer to the announcement date. This feature suggests two types of information structures, one where the secret is well-kept and one where significant preannouncement leakage occurs.

Our results from this section have several interesting implications. First, we find evidence (as have others before) of significant leakage of information ahead of merger announcements. Despite using quite different techniques, our findings are fairly consistent with that previous empirical literature. Second, we find evidence of significant heterogeneity across firms as to when this leakage begins. Together these findings suggest the inadequacy of traditional event study methodology, even employing large, uniform windows, if one is interested in estimating the full effect of a merger announcement on the value of a firm. Finally, our results suggest confirmation of many characteristics of the Kyle model. While beyond the scope of this paper and afield from its main focus, further testing of the Kyle model and other related theoretical models would be of interest.

5 Conclusion

In this paper we have considered three mechanisms by which information might be gradually revealed, diffused, and incorporated into stock prices, and have developed corresponding econometric techniques for evaluating and addressing this gradual movement in stock prices. We present two short applications showcasing these techniques and their relevance. Both the evolution of the Clinton health care reform proposal and the price movements ahead of tender offers were shown to be characterized by a gradual incorporation of information. Accounting for this gradual incorporation enabled us to assess the full impact of these events and also revealed elements of the price process.

These techniques should have wide applicability. Researchers interested in a policy issue can better assess the timing and impact of a policy change on stock prices. And understanding of the stock market's price formation process can be enhanced by applying these techniques to other settings in which private information may play a significant role.

Table 1: Pharmaceutical Companies Sample

Company	Ticker Symbol
Abbot	ABT
American Home Products	AHP
Bristol Myers Squibb	BMY
Barr Laboratories	BRL
Glaxo	GLX
ICN	ICN
Eli Lilly & Co.	LLY
Merck, Sharpe, & Dohme	MRK
Pfizer	PFE
Rhone Poulenc Rorer	RPR
Schering-Plough	SGP
Smithkline Beecham	SBH
Warner Lambert (Parke Davis)	WLA

Table 2: Traditional Event Study, Pharmaceuticals

Event Number	Estimate	Stand Err	T Stat
1	-0.0130	0.0100	-1.291
2	-0.0013	0.0100	-0.130
3	-0.0145	0.0100	-1.439
4	0.0025	0.0100	0.251
5	-0.0231	0.0100	-2.299
6	-0.0234	0.0100	-2.324
7	0.0005	0.0100	0.046
8	-0.0071	0.0100	-0.707
9	-0.0042	0.0100	-0.423

One-day event windows.

Table 3: Tender Offer Targets Sample

Company	Ticker Symbol
Aegis Corp.	AO
Amalgamated Sugar Co.	AGM
American Nat. Res.	ANR
ANTA Corp.	ANA
Applied Data Resh. Inc.	ADR
ARO Corp.	ARO
Bache Group Inc.	BAC
Brunswick Corp.	BC
Burgess Inds. Inc.	BGS
Cannon Mills Inc.	CAN
Cardiff Equities Corp.	CEQ
Caressa Group Inc.	CSA
Carnation Co.	CMK
Cenco Inc.	CNC
Cessna Aircraft Co.	CEA
Chieftain Development Corp.	CID
Chilton Corp.	CHN
Clausing Corp.	CLA
Coldwell Banker & Co.	CBC
Compugraphic Corp.	CPU
Connecticut Nat. Gas. Corp.	CNG
Conoco Inc.	CLL
Continental Airlines Corp.	CAL
Cox Communications Inc.	COX
Criton Corp.	CN
Dean Witter Reynolds Inc.	DWR
Delhi Intl. Oil Corp.	DLH
Donaldson, Lufkin & Jenrette Inc.	DLJ
Enstar Corp.	EST
Esmark Corp.	ESM
Faberge Inc.	FBG
Franks Nursery & Crafts Inc.	FKS
Friona Inds. Inc.	FI
Garfickel Brooks Bros Miller	GBM
Gas Svc. Co.	GSV
General Portland Inc.	GPT
General Steel Inds. Inc.	GSI
Getty Oil Co.	GET
G F Corp.	GFB
Giddings & Lewis Inc.	GID
Grand Central Inc.	GC
Gray Drug Stores	GRY

Table 3: Tender Offer Targets Sample, continued

Company	Ticker Symbol
Harsco Corp.	HSC
Heublein Inc.	HBL
Hobart Corp.	HOB
Informatics General Corp.	IG
Itek Corp.	ITK
James Fred S. & Co. Inc.	JMS
Juniper Petroleum Corp.	JUN
Kentron Intl. Inc.	KTN
Lane Bryant Inc.	LNY
Levi Strauss & Co.	LVI
Lowenstein M. Corp.	LST
MGM Grand Hotels Inc.	GRH
Malone & Hyde Inc.	MHI
Marathon Oil Co.	MRO
Marshall Field & Co.	MF
McGraw Edison	MGR
Mesa Royalty Trust	MTR
Mite Corp.	MTE
N I Industries Inc.	NIN
Nabisco Inc.	NB
Narco Scientific Inc.	NAO
Northwest Energy Co.	NWP
Northwest Inds. Inc.	NWT
Northwestern Mutual Life	NML
Norton Simon Inc.	NSI
Opelike Mfg. Corp.	OPK
Pacific Lumber Co.	PL
Pay Less Drug Stores NW	PAY
Peoples Drug Stores Inc.	PDG
Petrolane Inc.	PTO
Puritan Fashions Corp.	PFC
Real Estate Investment Trust America	REI
REDM Inds. Inc.	RED
Revlon Inc.	REV
Richardson Vicks Inc.	RVI
Rio Grande Inds. Inc.	RGI
SCA Services Inc.	SCV
SCM Corp.	SCM
Schlitz Jos. Brewing Co.	SLZ
St. Joe Minerals Corp.	SJO
St. Regis Corp.	SRT
Schrader Abe Corp.	AMS
Scovill Inc.	SCO

Table 3: Tender Offer Targets Sample, continued

Company	Ticker Symbol
Searle G. D. & Co.	SRL
Signal Cos. Inc.	SGN
Southland Rty. Co.	SRO
Spectro Inds. Inc.	SPO
Speed O Print Bus. Mach.	SBM
Sta Rite Inds. Inc.	SRE
Stauffer Chemical Co.	STF
Suburban Propane Gas Corp.	SPG
Sunbeam Corp.	SMB
Technicolor Inc.	TK
Texas Gas Res. Corp.	TXG
Texasgulf Inc.	TG
Thiokol Corp.	THI
Torin Corp.	TOR
Transway Intl. Corp.	TNW
Uniroyal Inc.	R
United Energy Res. Inc.	UER
United Rlty Invs. Inc.	URT
United States Inds. Inc.	USI
Unocal Corp.	UCL
Vulcan Inc.	VX
Walbar Inc.	WBR

Table 4: Kyle Model, Reduced Form

Regressor	Estimate	Stand Err	T Stat
$(v-p)_{1-10}$	0.0050	0.0020	2.527
$(v-p)_{11-20}$	0.0073	0.0023	3.173
$(v-p)_{21-30}$	0.0087	0.0027	3.231
$(v-p)_{31-40}$	0.0129	0.0032	4.043
$(v-p)_{41-50}$	0.0147	0.0039	3.788
$(v-p)_{51-60}$	0.0358	0.0052	6.859
constant	-0.0024	0.0007	-3.420

Dependent Variable is Δp_t, change in market adjusted prices. Estimated by OLS over $T = 60$ trading days. The standard errors are heteroskedasticity-robust.

Table 5: Results, Restricted Kyle Model

Parameter	Estimate	Stand Err	T Stat
ξ_0	0.0004	0.0004	0.883
γ_1	0.0293	0.0025	11.797
t_0	47.7859	0.6154	77.653

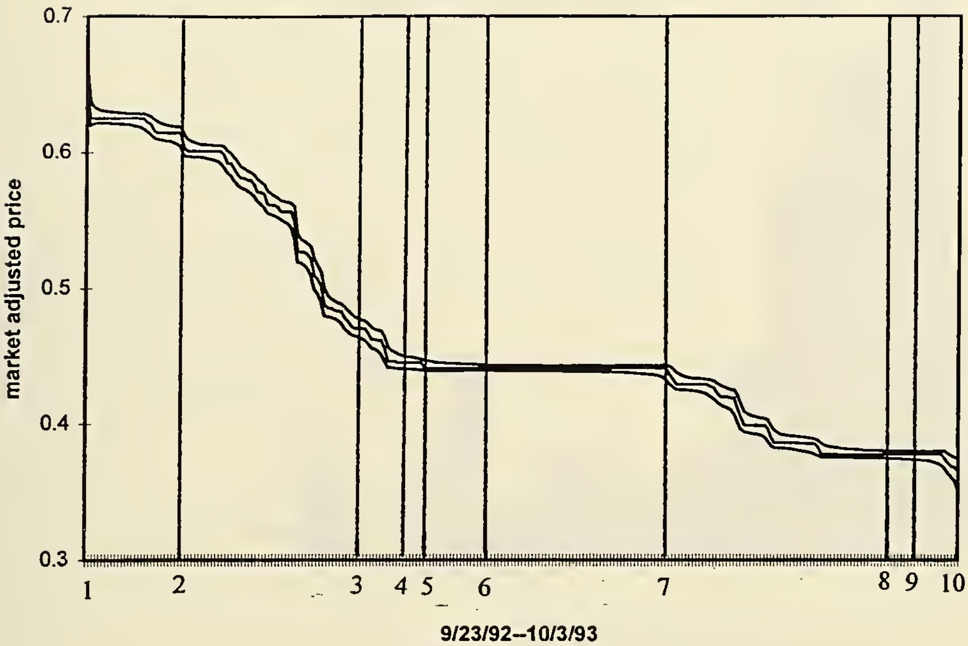
Dependent Variable is Δp_t, change in market adjusted prices. Estimated by Non-Linear Least Squares over $T = 60$ trading days. The standard errors are heteroskedasticity-robust.

Table 6: Results, Kyle Model

Parameter	Estimate	Stand Err	T Stat
ξ_0	0.0004	0.0004	0.907
γ_1	0.0005	0.0197	0.027
γ_2	0.0504	0.0209	2.414
t_0	46.0463	4.6260	9.954

Dependent Variable is Δp_t, change in market adjusted prices. Estimated by Non-Linear Least Squares over $T = 60$ trading days. The standard errors are heteroskedasticity-robust.

Figure 1: Isotonic Regression of Pharmaceutical Portfolio



1. Bill Clinton gives speech at Merck, September 24, 1992

2. Bill Clinton is elected, November 3, 1992

3. Hillary Rodham Clinton is named head of HCTF, January 25, 1993

4. Bill Clinton attacks pharmaceutical manufacturers for high prices, February 12, 1993

5. NYT reports HCTF is leaning towards regulating drug prices, February 16, 1993

6. Adverse earnings reports, March 24, 1993

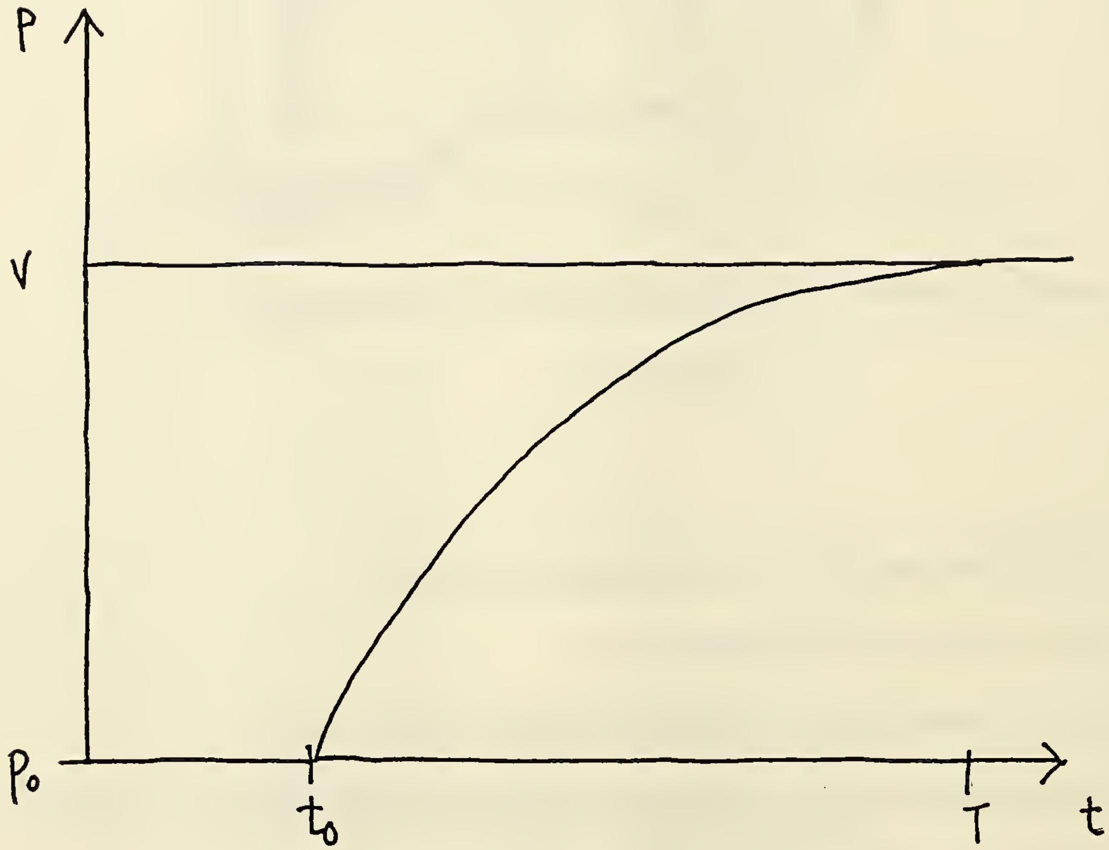
7. HCTF disbands, May 31, 1993

8. NYT anaylzes a leaked Clinton plan, September 11, 1993

9. Bill Clinton unveils health care reform proposal, September 22, 1993

10. Possible political high point of plan, October 3, 1993

Figure 2
Expected Price Path
(zero realizations of noise traders)



$$P_t = \begin{cases} P_0 & t < t_0 \\ V - c_1 e^{-c_2(t)t} & t_0 < t < T \end{cases}$$

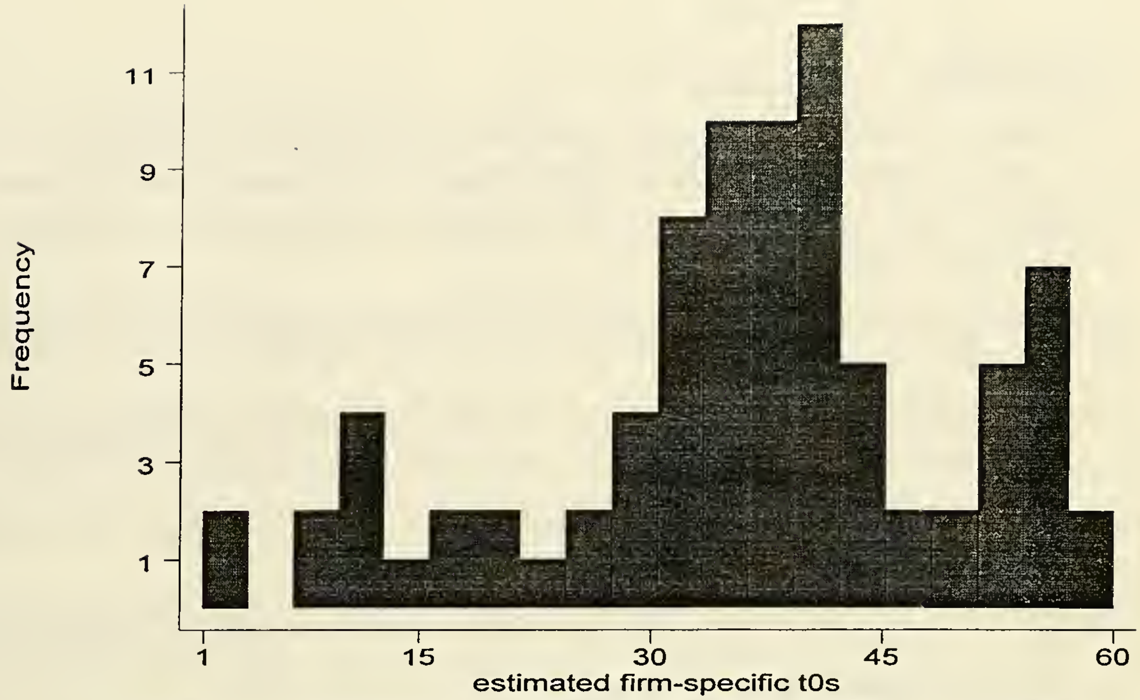


Figure 3: Histogram of Estimated Transition Times

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